

# CAAP Quarterly Report

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Project Title: *A novel structured light based sensing and probabilistic diagnostic technique for pipe internal corrosion detection and localization*

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For quarterly period ending: *Jan 7, 2018*

## **Business and Activity Section**

### **(a) Generated Commitments**

**Project abstract:** Internal corrosion in pipes is dangerous due to multiple factors contributing to its development. Degradation of the pipeline health is susceptible to hazard due to failure. To prevent such failures, a major challenge for the maintenance crew to detect and repair corrosion still prevails due to difficult and expensive accessibility during scheduled maintenance. The proposed method will focus on the development of novel structural light-based imaging for internal corrosion detection, which simplifies the detection process while achieving superior spatial resolution. The proposed approach will develop an endoscopic structured light scanning tool that is based on phase measurement profilometry (PMP). The developed system will be simple to fabricate and easy to be used by maintenance personnel with minimal skillset due to its intuitive scans. The structured light system will be developed to generate high-resolution reconstructed images representing surface texture with high accuracy. Based on the images, additional processing capabilities developed using Bayesian updating technique will give the capability of automatic classification and identification of different types of precursors. A convolutional neural network-based corrosion detection method will provide automated detection, which further minimizes the operator involvement. The uncertainty quantification technique will be integrated to enhance the probability of detection and to quantitatively determine the damage size and location.

Based on the identified challenges and state-of-the-art techniques, a complete solution is needed to detect, localize and evaluate internal corrosion in metal pipelines. Our proposed solution is to develop a phase measurement profilometry (PMP) structured light-based tool to detect and locate any surface defects and damages on the pipe wall, which includes specifically corrosion. Internal corrosion will be effectively detected and evaluated by checking the amount of material loss, color change, spread and pattern in the pipe wall simultaneously with a capability of integrating with ILI platforms. This optical inspection is also integrated with a set of numerical tools to evaluate structured light sensor information in order to automate the analysis of inspection data. The specific technical objectives/goals of the proposed research are:

- Design and develop a PMP structured light-based in-line inspection endoscopic scanner. The deliverables include:
  - design a new SL module to produce patterns with high resolution and contrast.
  - develop a new scheme to calibrate the new PMP based projector and camera(s).
- Develop a new reconstruction algorithm called moving phase measurement profilometry (MPMP) to exploit the system movement of the scanner along the pipe to enhance the quality of the reconstruction and detection.
- Evaluate the suitability of different optical methods like stereo cameras to enhance the performance of corrosion detection.
- Develop a convolutional neural network-based model for the automatic detection and classification of corrosion damages from the provided structured light sensor data to mitigate the need for manual analysis of 3D sensor massive data.
- Develop an uncertainty quantification technique to enhance the probability of detection and to quantitatively determine the damage size and location.

Educational Objectives: Another major objective of the proposed effort is to inspire, educate and train Ph.D. and MS students to address pipeline safety challenges, potentially as a career after their graduation. If funded, two Ph.D. students from both universities and several MS/undergraduate students will be included in this CAAP program. They will be trained and educated in science and engineering to address pipeline safety and integrity challenges. The PIs believe education is a critical component of the CAAP project, and we will integrate research with educational activities to prepare the next generation scientists and engineers for the gas and pipeline industry. Specific educational objectives include:

- Inspiring, educating and training the graduate students at MSU and ASU as research assistants for pipe integrity assessment and management. Our previous successful CAAP projects have produced several engineers, researchers and summer intern in gas and pipeline industry,
- Integrating research topics from this effort with the existing undergraduate research programs at MSU, e.g. ENSURE program at the College of Engineering and ASU to involve undergraduate students in pipe safety research.
- Improving the curriculum at MSU (e.g., Nondestructive Evaluation) and ASU (e.g., Machine Learning and Artificial Intelligence) using the scientific findings and achievement from the proposed research,
- Adapt research topics from this project to student projects in seminar, senior design, and project courses, in order to make educational impacts on broader groups of students,
- Encourage the graduate research assistants involved in this project and students in the courses to apply for internships at USDOT/PHMSA and industry to practice their learned skills and gain practical experiences in areas related to pipe safety and integrity.

The above-mentioned goals and objectives of this CAAP project will be well addressed and supported by the proposed research tasks. Development, demonstrations and potential standardization to ensure the integrity of pipeline facilities will be carried out with the collaborative effort among two different universities and our industry partner, Gas Technology Institution. This MSU-ASU-GTI team has successfully completed several PHMSA projects including “Slow Crack Growth” study, which was ranked No. 2 overall in all core PHMSA projects in 2017. The quality of the research results will be overseen by the PIs and DOT program manager and submitted to high-profile and peer-reviewed journals and leading conferences. The proposed collaborative work provides an excellent environment for the

integration of research and education as well as tremendous opportunities for two universities supported by this DOT CAAP funding mechanism. The graduate students supported by this CAAP research will be heavily exposed to ILI, NDE, reliability and engineering design topics for emerging pipeline R&D technologies. The PIs have been actively encouraging students to participate in past and ongoing DOT projects and presented papers at national and international conferences. Students who are not directly participating in the CAAP project will also benefit from the research findings through the undergraduate and graduate courses taught by the PIs and attending university-wide research symposium and workshop.

### **(b) Status Update of Past Quarter Activities**

#### **Task 0:**

The project kickoff meeting was held via teleconference and was attended by four teams from DOT, GTI, ASU, and MSU.

- DOT was represented by Robert Smith
- MSU team was led by Yiming Deng
- ASU team was led by Yongming Li
- GTI team was led by Ernest Lever, who will provide technical guidance and support.

A brief presentation was given by MSU and ASU to discuss the project objectives, methodologies, tasks structure, timeline, and deliverables. MSU will be responsible of developing the 3D vision system including the hardware and reconstruction algorithm. ASU will be responsible of developing the probabilistic model to analyze the 3D data and enable automatic fault detection.

#### *Discussion:*

The teams discussed the project objectives and the final expected deliveries. They also discussed the project execution plan and the collaboration between the different teams. In addition to that, the following issues were discussed during the meeting:

- GTI team gave input about the necessity of surface preparation before performing any 3D measurement for the corroded surface.
- GTI promised to provide flat and cylindrical corroded samples to help evaluate the performance of the tools during the development phase.
- Raised issues:
  - System integration to robotic platform
  - Field testing of the tools

#### **Task 1 – 3D Acquisition sensor design**

This task is specified to develop structured light-based scanning sensor for internal corrosion detection, which simplifies the detection process and decreases the scan time.

- Explore the suitability of stereo vision techniques for damage shape reconstruction.
- Develop an endoscopic structured light scanner.
- Fabricate an easy to use interface for intuitive scans.

#### **A. Reconstruction with Stereovision:**

Stereo-based 3D acquisition is one of the first methods used to reconstruct the shape of 3D objects since it mimics the human way of perceiving depth from 2D images. These systems use two cameras separated by a specific distance and share a large percentage of their field of view as shown in *Figure 1*.

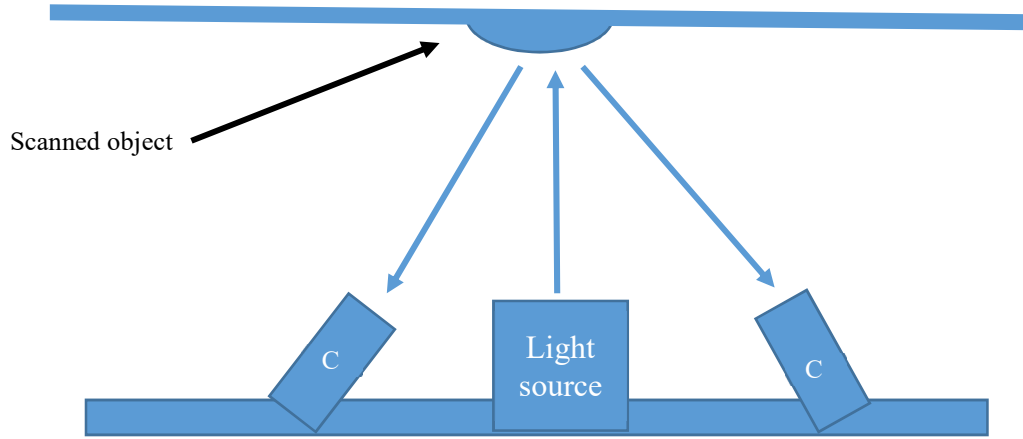


Figure 1: General stereo vision setup

The depth information is extracted by triangulating the disparity in the position of the observed objects in the two camera frames. This method works well in the presence of unique features that can be compared in both images. Therefore, it fails when there is a lack of unique comparable features in both camera frames [1]. A simulation environment was created to simulate the sensors in a controlled numerical environment. This setup gives the ability to test multiple types of optical equipments and test their performance before implementing them. The first model was used to simulate an ordinary stereo system with two cameras and a white light source. The scanned object is a half of sphere that has a smooth surface. The results in Figure 2 shows that the stereo algorithm fails when there is a lack of texture on the scanned object. One solution to deal with this problem is to introduce texture to the scanned object surface by adding a light source that can project a coded pattern on the scanned object.

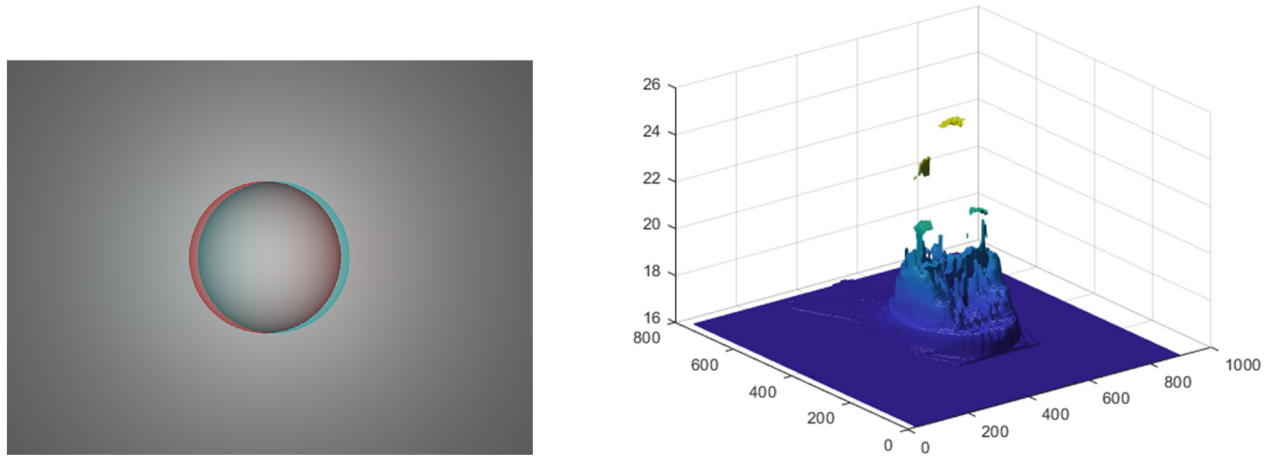


Figure 2: Reconstruction of simple stereo image: a) Overlaid images from the stereo camera, b) 3D reconstruction from stereo images

A simulated reconstruction with the added coded source is shown in *Figure 3*. In this case, the projector projects a random pattern on the scanned object surface. This pattern provides the required texture for matching the pixels blocks from the two stereo cameras and provide acceptable results even in the nonexistent of clear unique features on the scanned object.

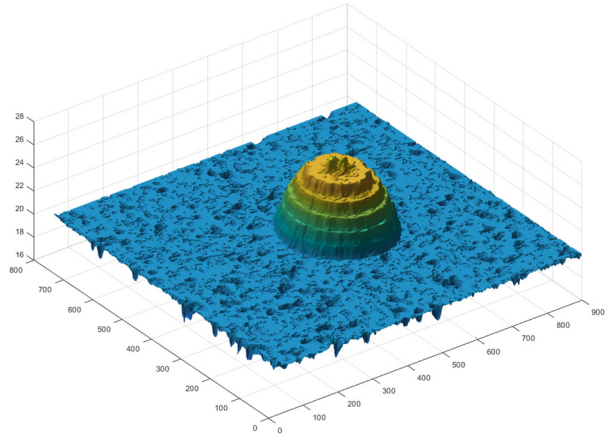
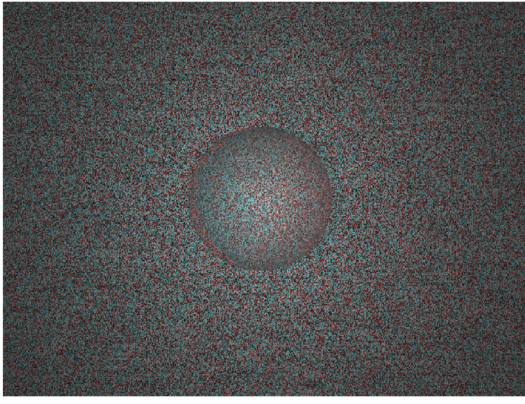


Figure 3: Reconstruction with stereo vision assisted with a coded light pattern: a) Overlaid images from the stereo camera, b) 3D reconstruction from stereo images

### B. Phase measurement-based sensor

The proposed approach is to develop a structured light scanning and data reconstruction tool that is based on PMP. However, the major novelty of this approach is to exploit the scanner/ILI tool movement to enhance the performance of the system. Current PMP based systems need to project at least three frames to reconstruct the surface while maintaining a static setup during the scanning process. This type of systems yields high accuracy 3D profiles (sub-millimeter accuracy) with a large number of 3D points that equal to the number of pixels in the camera frame [2]. The main drawback of the commercially available system is that it needs to be fixed at a spatial location during the scanning process, which means that it is challenging to be integrated with a moving scanning platform, such as ILI. The proposed approach will address this technical gap and take advantage of the movement for better corrosion detection. The structured light sensor consists of a light module that projects a unique light texture and a camera that captures the deformations in the projected pattern.

#### *Structured light in rectangular geometry:*

Ordinary phase shifting based structured light is based on projecting a sequence of  $N$  phase-shifted patterns with a phase difference of  $\theta$  between each two consecutive frames, like most of the commercially available systems do. Where  $\theta$  in most of their algorithms equals to  $2\pi/N$  or  $2\pi/(N+1)$  to provide more averaging effect. From those  $N$  phase shifted patterns, the phase of the imaged points can be estimated and calculated. The phase is then subtracted from the phase of a known baseline to calculate the depth of the scanned object. In traditional scanning platforms, the projected pattern is shifted while the scanning platform is fixed, and the pattern is shifted digitally so the amount of the phase shift created in the projected pattern is similar to the phase shift recorded by the camera pixels. The intensity of the projected pattern on the scanned object is given by:

$$I_n = I' + I'' \cos\left(\phi + \frac{2n\pi}{N}\right), \quad n = 0, 1, 2, \dots, N-1, \quad (1)$$

$I_n$  is the intensity of the camera pixel for shifted fringe,  $I'$  is the ambient light intensity and  $I''$  represents the modulation signal intensity. With only three shifted patterns and by assuming a constant ambient light, the phase ( $\phi$ ) at each image point is

$$\phi(x, y) = \text{atan}^{-1}\left(\frac{I_1 - I_3}{I_2 - I_1 - I_3}\right). \quad (2)$$

In our proposed platform, the entire scanning system (camera and projector) is moving in ILI while projecting a static fringe on the pipe inner wall. This movement will cause the projected pattern on the scanned object (pipe with internal corrosion and other types of damage) to be shifted by a distance  $dx$  resulting in a phase shift ( $\Delta\phi$ ) in the projected pattern that varies according to the height of the scanned

object. An experimental setup with a digital light projector and a camera was used as a test setup to verify the algorithm in rectangular geometry. The camera-projector setup was also mounted on a moving platform to simulate the movement of the setup inside a pipe as shown in Figure 4a. The sinusoidal patterns were generated by defocusing the square pattern in Figure 4b to avoid the projector nonlinearities. The resulted projected pattern on the scanned target is shown in Figure 4c.

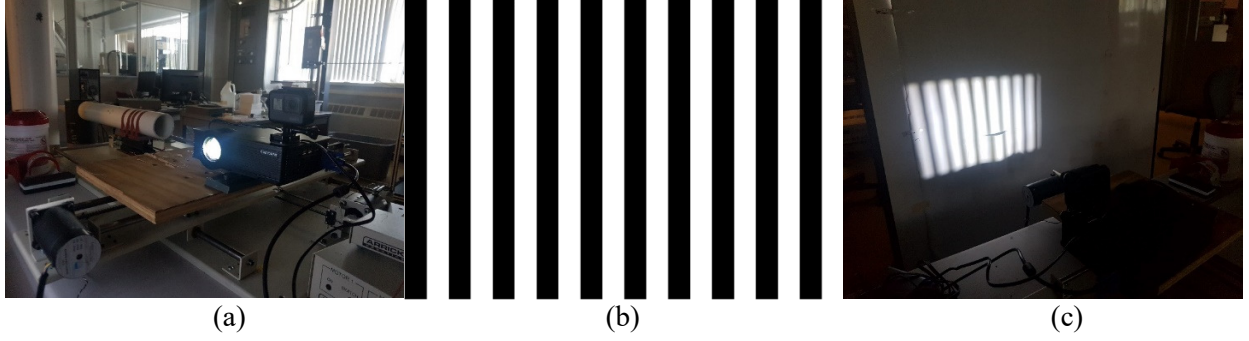


Figure 4: a) Camera-projector setup, b) Projected pattern, c) Defocused pattern from the projector

The first experiment was conducted by using the system as a PMP scanner by projecting multiple shifted sinusoidal patterns on the scanned object while having a static scanner. The 3D reconstruction of the scanned object is shown in Figure 5b. This 3D profile serves as a profile for the moving PMP experiment. For the moving PMP, the scanner was moved in a constant speed while projecting a static pattern onto the scanned object. The image stream from the camera was then registered to compensate the effect of the movement and the resulted sequence for consecutive frame is shown in Figure 6a. The 3D profile from the moving is shown in Figure 6b. When comparing it to the results from regular PMP, the MPMP algorithm was able to achieve similar reconstruction quality. There are some artifacts in the MPMP results that related to the non-constant phase shifting from the nonlinear relationship between the phase distribution on the pipe wall and the pipe diameter.

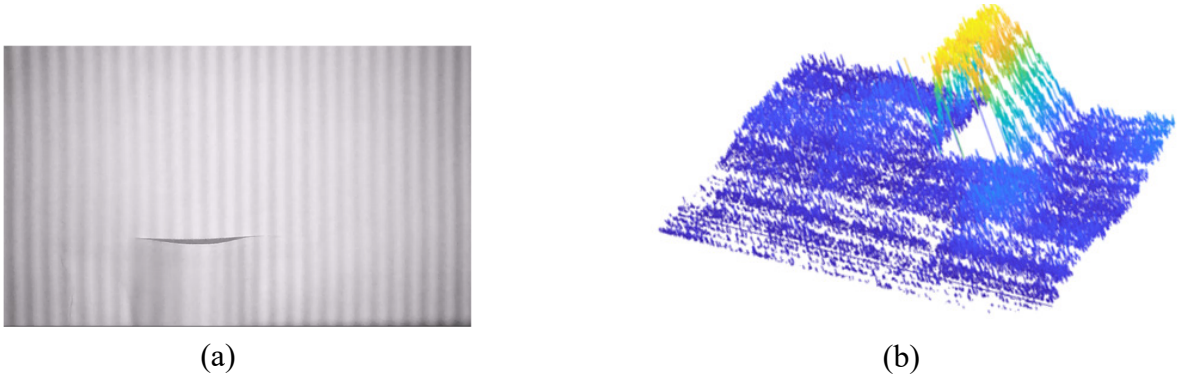


Figure 5: PMP scanning results: a) Sample image from the camera, b) Reconstructed 3D profile with PMP

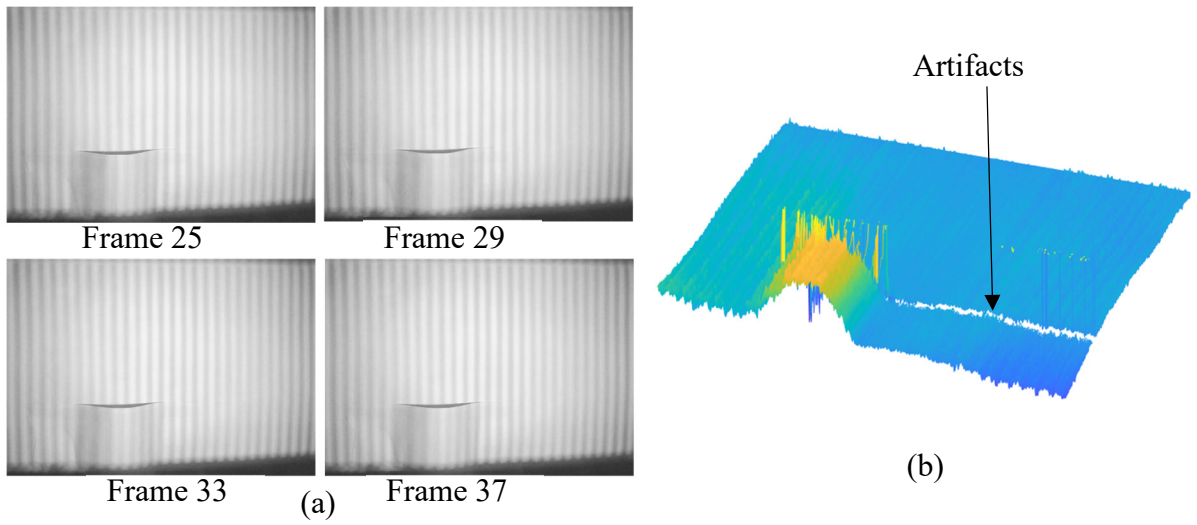


Figure 6: Reconstruction with moving the camera and static pattern: a) Images sequence from the moving camera, b) Reconstructed 3D profile with moving PMP

*Structured light is cylindrical geometry:*

The structured light setup is modified in order to scan the cylindrical geometry inside the pipe. In this scheme, the light module is placed in series with a camera that is pointing in the same direction as shown in Figure 7a. The triangulation process in the geometry at a specific angle ( $\theta$ ) is explained in Figure 7b. Here,  $c$  is the camera,  $p$  is the projector,  $P$  is the intersection point,  $f$  is the focal length,  $d$  is the distance between the projector and camera, and  $r$  is the position of the point on the image plane. For a general camera model, it is defined by  $f_p/Z = r_p/X$  and  $f_c/(z - d) = r_c/X$ . By combining the two equations, the coordinate of the point is extracted as:  $Z = \frac{d}{1 - \frac{f_c r_p}{f_p r_c}}$  and  $X = \frac{r_p Z}{f_p}$ .

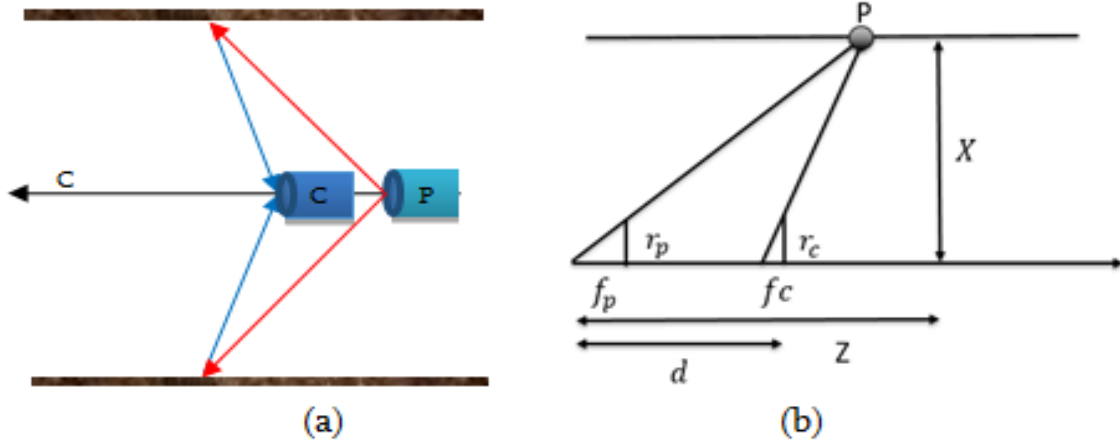


Figure 7: a) Proposed schematics for sensor design, b) Triangulation of the system in cylindrical coordinates.

Projecting a pattern with linearly changing phase results in a nonlinearly distributed phase on the pipe internal walls as shown in Figure 8a. The nonlinear distribution arises from the nonlinear relation between the distance from the camera and the change in the camera coordinates according to the camera equation. Nonlinear distribution of the phase along  $z$  causes different phase change for each projected point when the system moves inside the pipe. Therefore, the phase change relationship in the rectangular domain will not valid. This problem is mitigated by projecting a pattern with nonlinearly distributed phase as shown in Figure 8b.

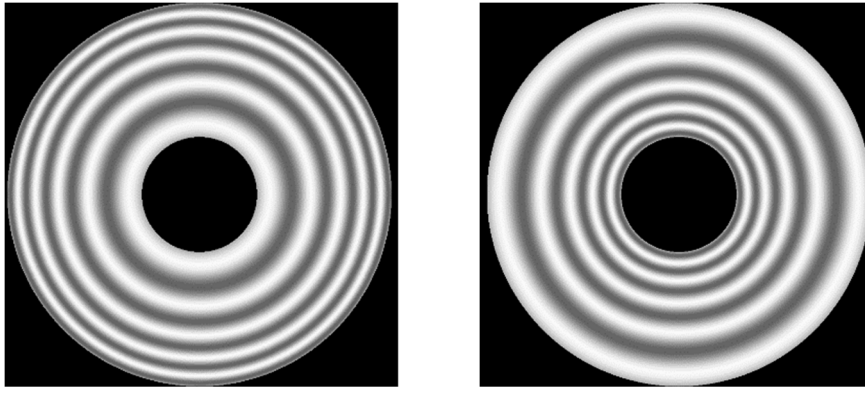


Figure 8: a) Projection of uniform pattern inside a pipe, b) Proposed phase nonlinear phase

A simulated reconstruction of a bump that is caused by external force is shown in Figure 9. A static nonlinear pattern is projected on the pipe wall, and then the scanner system is moved into the pipe while the camera continue to image the pipe wall. In this case only three frames are registered, and the phase is then extracted according to Equation 2. The defect on the pipe wall was reconstructed successfully but with some artifacts. Similar to the rectangular geometry case, the artifacts are related to the non-constant phase shifting from the nonlinear relationship between the phase distribution on the pipe wall and the pipe diameter.

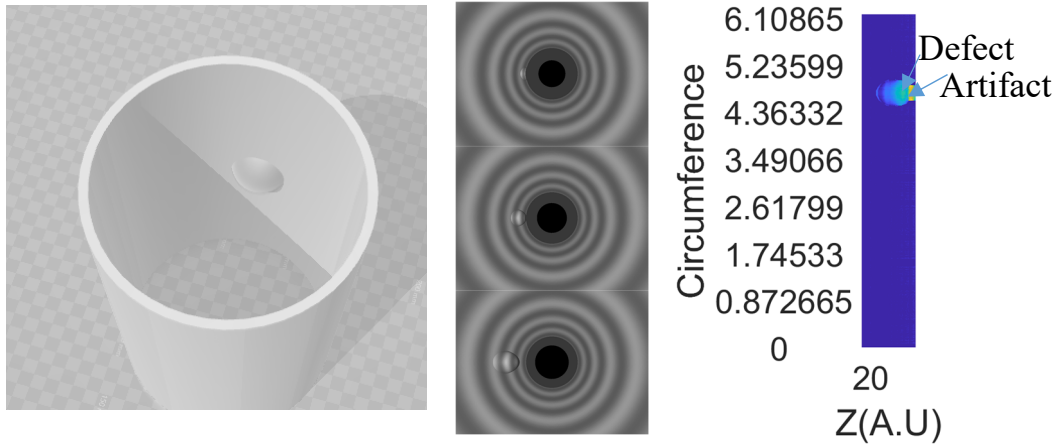


Figure 9: Simulated 3D reconstruction bump defect on the pipe internal surface

### Discussion and future work:

During the past quarter, the concept of moving PMP was validated experimentally in rectangular geometry and the algorithm was tested in cylindrical geometry by using numerical simulator. Stereo vision was investigated, and the active stereo vision system shows promising results. Future work will continue to test both the PMP and stereo algorithms in cylindrical geometry while continuing the hardware development.

### Task 3. Automated corrosion detection and uncertainty quantification

#### Summary

The transmission gas pipelines are dominantly made of carbon-iron materials. Unlike the plastic materials widely used in distribution pipes, iron materials are subject to corrosion by the presence of carbon dioxide ( $\text{CO}_2$ ), hydrogen sulfide ( $\text{H}_2\text{S}$ ) and free water in oil and gas pipelines [3]. Corrosion inside the pipe can cause the loss of pipe mass, the head loss and polluting the transmitting fluid [4,5]. In this research we are focusing on the detection, mitigation and localization for the corrosion damage in inner pipe wall.

The primary task for ASU is the automated corrosion detection and uncertainty quantification. The damage detection is based on the image data generated using the hardware device developed by MSU. In this report, previous work in the damage detection in polymer pipes based on imagine method is reviewed. In the previous ASU-MSU collaboration, an automated damage detection and classification algorithm has been developed. It uses the 3D reconstructed surface structure of the pipe to generate geometric features. These features are used to classify different types of damage using Bayesian classifier. The damage type in the previous study mainly focused on physical caused damage such as indentation, impingement, squeeze-off and slit. Since the image data for corrosion damage is not available in large quantity, the old damage image, both simulation and lab-created damage, are used to test the Neural Network (NN). Preliminary result will be shown in the following discussion.

## Content

### Geometric feature based damage classification

Using the structured light technique, the series of 2D images can be used to reconstruct the 3D surface of the pipe inner wall. The geographic features can be extracted by comparing the 3D reconstructed damaged pipe with a perfect pipe. In Figure 10 showed the simulated 3D damaged pipe (left four) and the lab-generated pipe damage reconstructed using optical images. The process for collecting real damage 3D image is a laborious work. So the simulated data were mostly used in the early stage of the research.

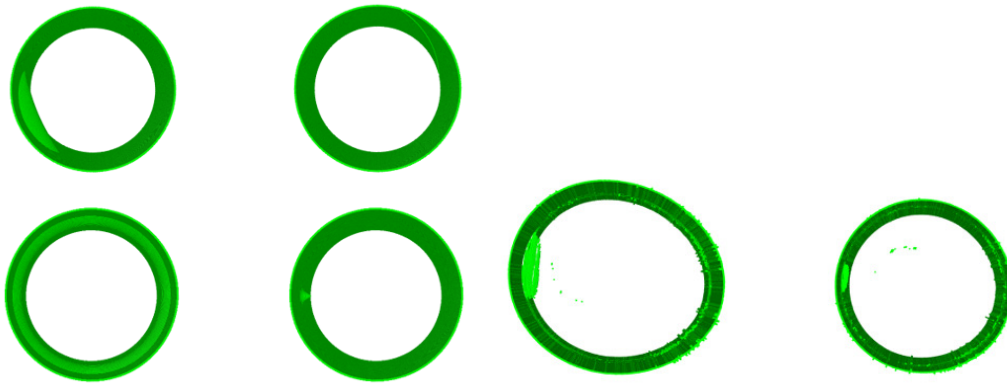


Figure 10. Simulated pipe damage in 3D (left four) and reconstructed lab-generated damage

In the previous research, by isolating the damage we are able to extract geometric features such as the surface area, the maximum cross section area, the length along the pipe direction and the aspect ratio of the damage. 400 data instances were generated with simulated pipe damage. The classification was done based on these features using Naïve Bayes classifier. Naïve Bayes (NB) classifier has the simplest network structure with one class node and several feature nodes. All feature nodes are assumed to be independent. The training data are used to train the likelihood function given each class. Class for testing data are assigned to the one that can achieve the highest posterior probability. As given in Eq. 1 [6]:

$$c^* = \arg \max_{i=1 \dots m} P(c_j) \prod_{i=1}^n P(A_i = a_i | c_j) \quad (1)$$

The network structure can be seen in Figure 11. Figure 12 showed the average classification accuracy vs. the training set size. We can see that the accuracy for this data set is around 89%.

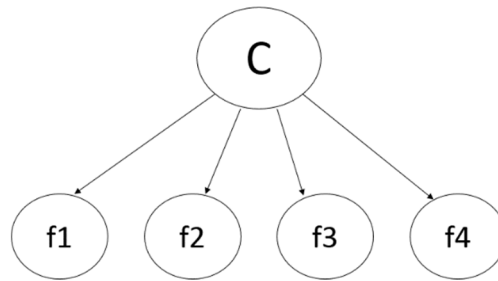


Figure 11. Graphic model for a Naïve Bayes classifier

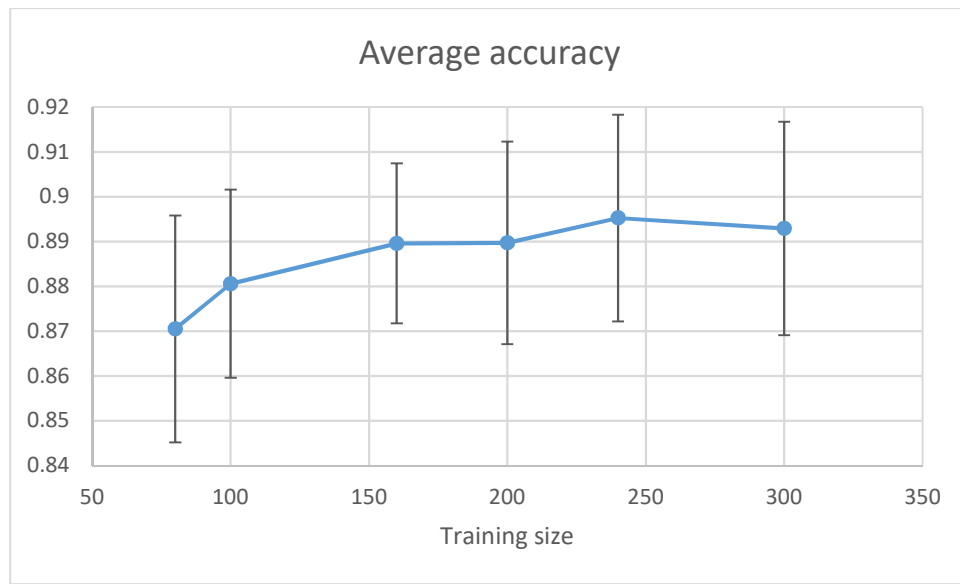


Figure 12. Average accuracy vs. training data size

To test out this algorithm, 90 sets of lab-generated damage data were collected using the hardware device. The data set covers three types of damage, namely slit, indent and impingement. The same processing and feature extraction were done to the real data. The classification using NB classifier is plotted in **Error! Reference source not found..** By varying the size of the training data, the average accuracy is around 77%.

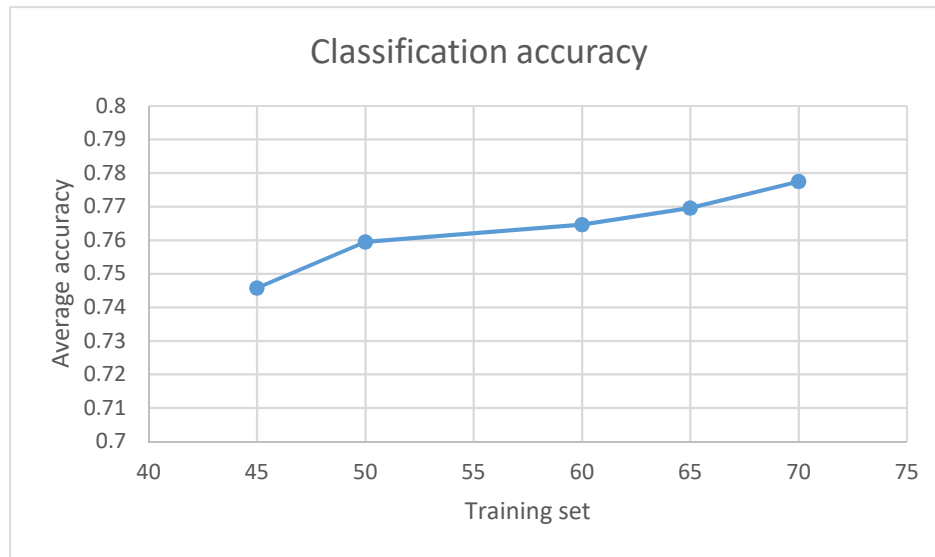


Figure 13. The average accuracy vs. training size using real data

### Damage classification using Convolution Neural Network (CNN)

In this part, Inspection V3, a CNN model from Google, was trained with 2D images to categorize damage modes. Convolutional neural network is an artificial neural network that was inspired by biological process of neurons. When an image is feed through the network, it will use the convolutional layers to apply a mathematical operation, extracting the essential characteristics, then passing the result to the next layer. At the final layer, the model will determine the extracted and condensed information from previous layers will be passed to the final output layer to determine what's in the image [7]. The performance of Inception V3 has been proven through the ImageNet Large Scale Visual Recognition Challenge where its "top-5 error rate" was at a stunning 3.46% [8]. The structure of the model used for this experiment is outputted using TensorBoard and shown in Figure 14. Retraining the full model is a complicated task that takes weeks to finish. Researchers from UC Berkeley and ICSI discovered that deep neural network models that has been pre-trained on ImageNet can also be applied to new tasks with limited training data

and deliver great result. This is because through the ImageNet training, the model was able to learn and identify the critical features that can usually be applied on the new tasks as well [9]. For practical tasks such as identifying pipe damages, it's more cost effective to retrain only the bottlenecks of the model. Bottlenecks refer to the final convolution layer of the model [8]. Retraining the bottleneck can effectively tailor the model to the specific set of images that needs to be recognized.

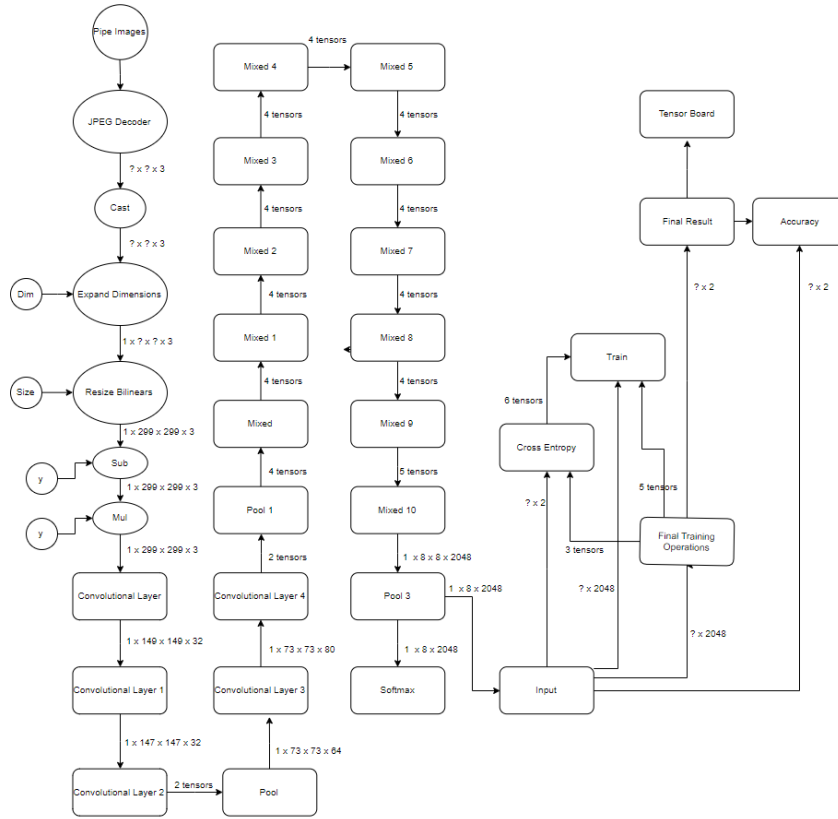


Figure 14. Inception V3 network structure.

The images used includes the simulated image and lab-generated image from the previous studies and some clips from online videos. Some sample images can be found in Figure 15. These images are photos shot at the inner pipe with a laser ring projector. The change in the shape of the laser ring indicates possible damages in the pipe. The network model will be tuned with five parameters to test its performance, including training steps, learning rate, batch size, training data size and noise of the training data.

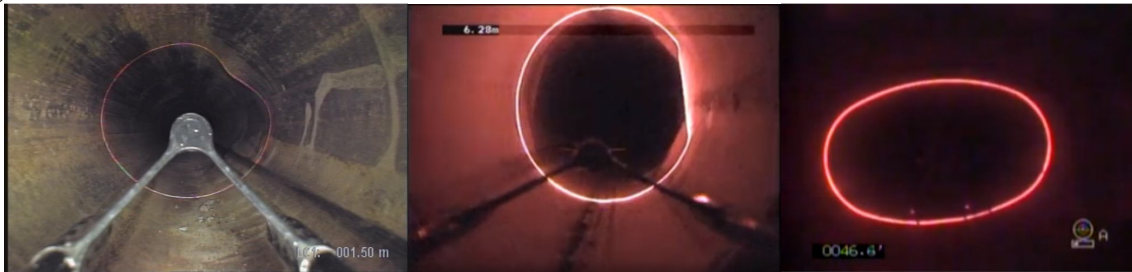


Figure 15. Sample images from online video screenshot

Now the quantity of images is enough for training a CNN model. Table 1 showed the number of images used for each training size. The size of the validation set is always 10% of the training set, while the test set stays consistent at 1000 images.

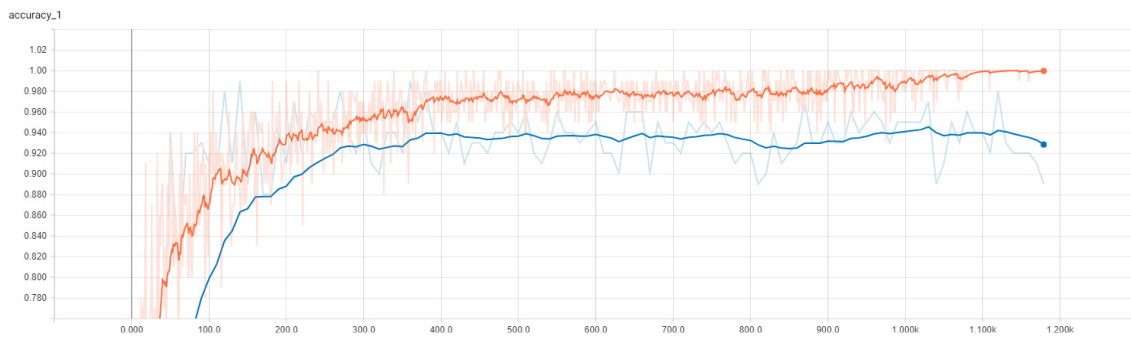
Table 1. Number of images used for training and testing

Training Set Size	Validation Set Size	Testing Set Size	Total Images
200	20	1000	1220
500	50	1000	1550
1000	100	1000	2100
2500	250	1000	3750
5000	500	1000	6500
7500	750	1000	9250
10000	1000	1000	12000

By running the network model with different parameter values, the optimal model can be found. Table 2 shows the parameters for the optimal model. The performance of the optimal model is plotted in Figure 16.

Table 2. Parameters for the optimal model

Training Steps	Learning Rate	Batch Size	Training Data Size	Noise	Test Accuracy	Training Time
1180	0.01	100	200	0.2	87.2%	2:06



a)

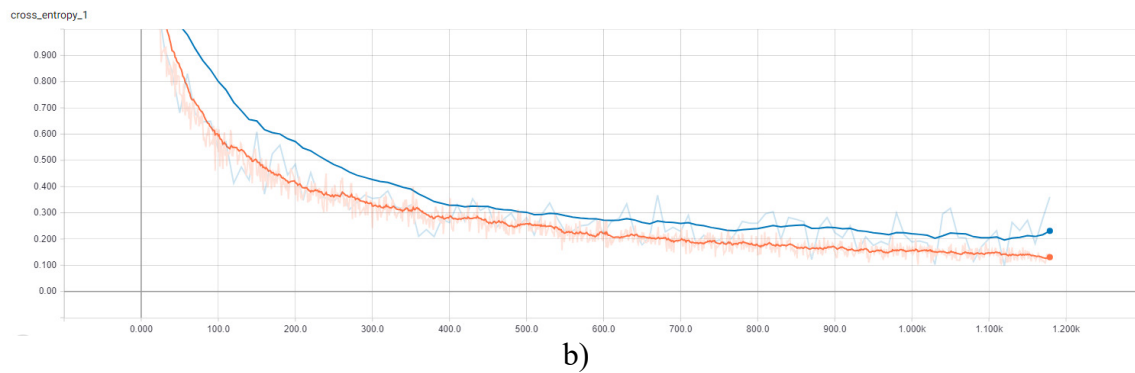


Figure 16. a) The training (orange) and validation (blue) accuracy and b) training (orange) and validation (blue) cross entropy of the optimal model.

Comparing with the damage classification based on geometric features, the accuracy using CNN model is much accurate. This is because the geometric features are a highly processed data during which the information may be lost. While the CNN method used 2D images as input and could utilize more information.

### Conclusion and future work

The work that has been done includes: The damage classification using damage geometric feature via Naïve Bayes classifier; The damage classification using 2D pipe image via Convolution Neural Network. It can be easily seen that the CNN approach can achieve higher accuracy. Although the pipe damages studied in this case is physical damage in polymer pipes, the CNN showed promising result in identifying such damage. The team will continue in this path and apply the method in the detection of corrosion damage. ASU will work closely with MSU on developing the imagine technique for the reconstruction of pipe damage. The damage detection will be extended to 3D cases. The uncertainty quantification will focus on the enhancement of the detection and localization accuracy.

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